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Jacob Kim-Sherman | Lee Seltzer

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Abstract

Empirical research in climate economics often relies on panel regressions of different outcomes on disaster damages. Interpreting these regressions requires an assumption that error terms are uncorrelated across counties and time, which climate science research suggests is unlikely to hold. We introduce a methodology to identify spatial and temporal clusters in natural disaster damages datasets, and show that accounting for clustering affects observed economic effects of disasters. Specifically, counties tend to experience 0.45% more disaster damage for every 1% increase in damage across other intra-cluster counties. Moreover, accounting for clustering makes some hazard types, such as droughts, appear more damaging.

JEL classification: Q50, Q54
Key words: natural disasters, clustering

Kim-Sherman, Seltzer: Federal Reserve Bank of New York (emails: jacob.kim-sherman@ny.frb.org, lee.seltzer@ny.frb.org). This paper was previously circulated under the title “Clustering in Natural Disaster Losses.” The authors thank Tim Park, Hyeyoon Jung, Viral Acharya, Julian Di Giovanni, Matteo Crosignani, Martin Hiti, and Jose-Luis Cruz for useful comments and discussion.

In September 2024, Hurricane Helene struck the United States, triggering Federal Emergency Management Agency (FEMA) disaster declarations across five states (Alabama, Florida, Georgia, North Carolina, and South Carolina). CoreLogic estimated that the disaster caused $47.5 billion in damage, including $20–$30 billion in uninsured flood losses. Mere weeks later, Hurricane Milton also hit Florida.[1] Since disaster relief resources are finite at the local level, a storm as massive as Hurricane Helene likely inflicts more damage on a given county if its neighboring counties have also been affected. Additionally, it is possible that since Helene had occurred in the recent past, Florida counties may have been more adversely affected by Hurricane Milton. In this paper, we propose a framework to account for how the effects of disasters may be correlated across space and time. This approach can be used to answer such questions.

In previous work in economics, most research on natural disasters has utilized county-by-month-level data to run panel regressions of different economic outcomes on disaster damages.[2] The regressions often make use of county and time fixed effects while clustering standard errors at the county level. Interpreting these regressions requires an assumption that the error terms are uncorrelated across counties and months. At the same time, the climate science literature finds consistent evidence for the idea that natural disaster occurrences are correlated over space and time, where disasters tend to be concentrated either in certain regions or in short windows of time.[3] Given this additional context from the climate science literature, the tendency of disaster damages to be spatially/temporally correlated could pose a threat to the assumption of uncorrelated error terms. This paper integrates this potential spatial and temporal correlation in the occurrence of natural disasters, which

[1]CNN Business: As Hurricane Milton threatens the US, Helene could cost property owners more than $47 billion.

[2]See, for example, Gallagher and Hartley (2017); Bleemer and van der Klaauw (2019); Billings et al. (2022); Gallagher et al. (2023); Kruttli et al. (2023); Correa et al. (2022); Blickle et al. (2021); Sastry (2021); Blickle and Santos (2022); Issler et al. (2021); Sastry et al. (2023); Deryugina (2017); Acharya et al. (2022); Tran et al. (2020); Bakkensen and Barrage (2018)).

[3]See, for example, Wheater et al. (2005); Li et al. (2016); Fu et al. (2023); Merz et al. (2021); Leonard et al. (2014); Zscheischler et al. (2018, 2020); Woodruff et al. (2013); Marsooli et al. (2019); Sarhadi et al. (2018)).

we refer to as "*clustering*," into the economics literature.

There are numerous reasons why clustering could have important implications for economic research. For example, if neighboring counties use the same resources to aid in recovery, these resources may be strained if all neighboring counties are affected by contemporaneous disasters. Additionally, counties may be less prepared for a disaster in the wake of another recent disaster. On the other hand, if different counties are exposed to common disaster risks, they can share adaptation and mitigation resources, potentially allowing them to better prepare for disasters. To allow researchers to consider these effects, this paper develops algorithmic approaches to identify spatial clusters (i.e., clusters across counties), temporal clusters (i.e., clusters across time), and spatiotemporal clusters (i.e., clusters across counties and time). To understand the implications of accounting for natural disaster clustering, we compare data on natural disaster damages aggregated to the cluster level to data on natural disaster damages aggregated to the county level.

Our analyses reveal three key facts about clusters in natural disaster damages. First, we find a positive relationship between the relative size of a disaster cluster (measured by the number of counties contained in the cluster) and the amount of damage. In particular, the average logged damage for all clusters in the 60th percentile and below is about 10 ($22 million). This is because there is little variation in cluster size at this point in the distribution, with the median cluster having a size of one county. However, at around the 60th percentile of cluster size, there is a sharp increase in disaster damages, and the average logged damage for the 95th percentile bin reaches about 15 ($3.3 billion). This suggests that an increase in relative size predicts a sharp increase in the expected level of damage, especially among very large clusters. Similarly, the distribution of the natural log of damages is more positive when examining cluster-level damages than county-level damages.

Second, we find that certain hazard types appear more severe when using a clustered approach than when using county-by-month-level data. Specifically, when examining summary statistics according to hazard type in county-level data, droughts are the ninth most severe hazard. However, similar summary statistics aggregated to the spatial cluster level show that droughts are the second most severe hazard type. This illustrates that analyzing natural disasters at the county level may have led researchers to understudy certain hazard types.

Lastly, we find that county-level damages tend to be larger when the county is part of a cluster that experiences more damage. In particular, a county typically experiences about 0.45% more disaster damage if all the other counties in the same disaster cluster experience an additional 1% of damage. While not causal, this result could suggest that, because of strained resources, counties face greater damages from disasters when their neighbors experience the same disasters. We also find that these results are especially acute for certain hazard types, such as floods, hurricanes and wildfires.

To summarize, this paper introduces a methodology to incorporate spatial and temporal correlation in the occurrence of natural disasters into empirical economic research. We provide an approach to identify natural disaster clusters. We show that incorporating clustering into analyses increases the estimated severity of the most severe natural disasters, as well as the estimated severity of certain hazard types such as droughts. We also confirm that county-level disaster damages are higher when the rest of the cluster also experiences higher damages. These findings indicate that clustering could be important for assessing economic outcomes following disasters.

In the first section, we describe the data sources used and define the clustering methodology. In the second section, we examine data on cluster-level damages in comparison to data on county-level damages, and test how county-level damages are correlated to damage experienced by other counties in the same cluster. In the third section, we discuss the implications of our clustering analysis for future research. In the fourth and final section, we conclude.

1 Data and Methodology

1.1 Data

The primary dataset used in our analysis is the Spatial Hazard Events and Losses Database for the United States (SHELDUS). SHELDUS provides information on the incidence of natural disasters at the county-by-hazard type-by-month level from 2000 until 2020 across 3,249 distinct counties in the United States.[4] While we focus on SHELDUS, as it is the most widely used dataset on natural disasters in economic research, this approach could be easily adapted to other county-level datasets on natural disaster damages. The methodology could also readily be used for any other type of data on negative outcomes experienced due to natural disasters by individuals, firms or municipalities.

These data include the type of natural disaster, categorized into 18 distinct hazard categories, as well as damages (divided into property and crop damages). For control variables, we use the Quarterly Census of Employment and Wages (QCEW) county-level dataset from the Bureau of Labor Statistics on wages, annual county-level datasets on population from the Census Bureau's American Community Survey (ACS) and county GDP from the Bureau of Economic Analysis for the period between 2000 and 2020.

1.2 Methodology

Most research designs that rely on a county-by-time-level panel require an assumption that the error terms are uncorrelated across counties and time.[5] However, the climate science literature presents several important challenges to such an assumption.[6] Some counties may be unconditionally more likely to experience certain types of disasters. For instance, Florida counties experience more hurricanes than average, and California counties experience

[4]While SHELDUS also provides data at the natural disaster level, we use the county-by-disaster-type-by-month panel as it is the format most commonly used by researchers.

[5]A detailed literature review on natural disasters in economics is provided in Internet Appendix IA.A.

[6]A detailed literature review on natural disasters in climate science is provided in Internet Appendix IA.B.

more wildfires than average. Additionally, if a county's neighbor experiences a disaster, this may raise the probability that the county itself experiences a disaster at the same time. If both counties are hit at the same time, this simultaneity could potentially exacerbate the strain on economic resources for each individual county. The climate science literature also suggests that if a disaster lasts longer, this could exacerbate adverse economic consequences of the disaster. These challenges to the assumptions of uncorrelated error terms motivate the development of a methodology to algorithmically identify common patterns of natural disasters, so that we can properly account for the correlation between disasters across space and time. We thus propose the following approaches for identifying common patterns of disasters in county-by-month-level data.

1.2.1 Spatial Clustering

Consider a given county i in a given period t. We can define the following function $H(c_t^i)$ as outputting the set of hazards $H_t^i = \{h_m, ..., h_n\}$ where h_m denotes a hazard experienced by county i in time t. For example, the event experienced by Harris County, Texas in August 2017 (when Hurricane Harvey took place) can be described as $H(c_{2017m8}^{\text{Harris, TX}}) = \{$hurricane, flooding, tornado, thunderstorm$\}$. Trivially, if c_t^i is not experiencing any hazards, this set would be the empty set.

We identify two counties (i, j) as having a *proximate common climate pattern* in time t if they are geographically contiguous and have at least one common hazard:

$$PCCP(i,j) = 1 \text{ if counties } i \text{ and } j \text{ are adjacent and}$$
$$H_t^i \cap H_t^j \neq \emptyset.$$

where H_t^i and H_t^j are defined as above. Consider the example of two neighboring Texas counties, Harris and Montgomery, which were both hit by hurricane, wind and flooding events in August 2017. Since Harris and Montgomery are adjacent, and $H_{2017m8}^{\text{Harris, TX}} \cap H_{2017m8}^{\text{Montgomery, TX}} =$

$\{$hurricane, flooding$\} \neq \emptyset$, we would say that $PCCP$(Harris, TX; Montgomery, TX) $= 1$.

We define two counties (c^i, c^j) as sharing a *common climate pattern* if there is a "path," with a distance of n counties, from county i to county j where the intermediate counties are (pairwise) proximate common:

$$
\begin{aligned}
CCP(c^i, c^j) = & 1 \text{ if } \exists \text{ a set of counties, } \{k_1, \cdots, k_n\} \text{ such that} \\
& PCCP(c^i, k_1) = 1 \text{ and} \\
& PCCP(k_1, k_2) = 1 \text{ and} \\
& \ldots \\
& PCCP(k_n, c^j) = 1.
\end{aligned}
$$

A *spatial cluster* is defined as the largest possible set of counties in time t that corresponds to a common climate pattern, following the inductive process until no more proximate common climate patterns can be identified.

As an example, Figure 1 applies the spatial cluster algorithm to the case of Hurricane Harvey. Panel (a) displays the generated spatial cluster containing Harris County, Texas, in August 2017 (i.e., the spatial cluster associated with Hurricane Harvey), while panel (b) shows all counties which were included in the Presidential Disaster Declaration for Hurricane Harvey. The spatial cluster identified by our algorithm closely aligns with the Hurricane Harvey Presidential Disaster Declaration. Most discrepancies arise from counties where a presidential disaster was declared, but ultimately, zero damages were reported.[7]

[7]Comparing the 63 counties identified by the clustering approach in this spatial cluster to the 75 counties identified in a Presidential Disaster Declaration (PDD) in August 2017 with the name "Harvey", we find an intersection of 60 counties (80% of the counties identified in the PDD). All of the 15 counties (the remaining 20%) identified in the PDD that are not a part of the cluster report zero damages in the SHELDUS dataset. Of these, three highly populated counties that did not experience damage (Dallas, Tarrant, and Travis) were added by Governor Abbott because they were sheltering a significant number of evacuees.

1.2.2 Temporal and Spatiotemporal Clustering

Much of the conceptual framework developed for identifying spatial clusters can be easily mapped to temporal clustering. We can identify a given county as having a *temporally persistent climate pattern* if it experiences the same climate hazard in at least two consecutive time periods:

$$TPCP(i,t) = 1 \text{ if } H_t^i \cap H_{t+1}^i . \neq \emptyset$$

This concept can be applied to combine spatial clusters in two consecutive time periods if at least one county experiences a temporally persistent climate pattern in both clusters. When this link can be established, the most expansive possible set of all of the counties experiencing proximate common and temporally persistent climate patterns is defined as a *spatiotemporal cluster*. We provide an extension of the Hurricane Harvey example to a spatiotemporal cluster in Figure IA.1, alongside the temporal evolution of this cluster in Figure IA.2. Note that the results in the main text will focus on spatial clusters, although the Internet Appendix contains analogous results for spatiotemporal clusters.

This approach is readily implementable in any statistical software such as Stata, Python, R, or Matlab. When executing the clustering algorithm, we classify the 161,664 county-months in which hazard damage occurs to 37,296 spatial clusters and 28,495 spatiotemporal clusters.

Summary statistics on disasters, using both data at the cluster level and at the county level, are displayed in Table IA.1. The size of the average cluster is about 4 counties. The average cluster's total damage is $17.5 million. On the other hand, the median total damage is only $23,600, indicating that the distribution is positively skewed.[8] The total damage numbers include both property and crop damages, although property damages contribute to 90% of the total damage. This could lead to analyses using SHELDUS data understating

[8]These summary statistics include events in SHELDUS with zero damage recorded, although they look similar when excluding the zero-damage events.

hazard types that result in relatively more crop damage than property damage, such as heat. All results in the main text are based on total damages, although results for specific damage types are included in Internet Appendix IA.C.[9]

This section has provided a description of our new approach to identifying clusters of natural disasters using data on natural disaster damages. In the next section, we will explore cluster-level disaster damages, to better understand how the choice of whether to examine disasters using county-level data or cluster-level data could impact the conclusions of researchers.

2 Comparing Cluster- and County-Level Damages

In the previous section, we described the clustering methodology we developed for this analysis. In this section, we will compare the cluster-level data on natural disaster damages with the county-level data on natural disaster damages. We will also examine whether counties tend to experience greater disaster damage when they are part of clusters that experience more severe disasters.

2.1 Exploring disaster-level distributions

To visualize the distributions of damage according to the approach used, panel (a) of Figure 2 displays the histogram showing the distribution of logged damages measured at the county level, overlaid with the distribution of logged damages at the cluster level. The right tail of the cluster-level distribution has substantially more mass than that of the county-level distribution.[10] All appear similar to the result shown in the main text.

[9]Note that by construction, the cluster-level distribution of damages will have more extreme values than the county-level distribution due to the effect of scaling. For this reason, all analysis in the paper making comparisons between counties and clusters will use the natural log of damage, to reduce the effects of outliers. Regression analyses also include an adjustment for the number of county-hazards experienced in a given cluster.

[10]Two-sample Smirnov (1939) equality of distribution tests confirm that these two distributions are statistically different at the 1% level.

The histograms show that the clusters with the most damage tend to have more extreme values than the counties with the most damage. One potential explanation for this could be that disasters covering larger areas tend to create more damage, and examining natural disasters in the form of a cluster allows you to observe this effect. To directly study whether disasters affecting more counties yield more damage, we study heterogeneity in cluster damages according to the cluster's size. Specifically, we sort clusters into percentile bins according to the number of counties contained in each cluster. Then, within each cluster, we calculate the average logged-damage. The results are displayed in panel (b) of Figure 2. There is little variation in disaster damage according to cluster size up until the 60th percentile, averaging about $22 million, as all clusters up until this point only have one county. However, disaster damage increases beyond this point, eventually reaching an average damage of $3.3 billion at the 95th percentile. This highlights both that the cluster-level distribution of disaster damages includes some disasters with very large amounts of damage, and that larger clusters tend to have more disaster damage. Figures IA.3 and IA.4 display similar plots using property and crop damages, and Figure IA.5 displays similar plots using spatiotemporal clusters. All appear similar to the main set of results.

To study how disaster distributions appear differently according to the type of hazard observed, we next examine detailed summary statistics by the type of hazard. Table 1 displays the distribution of disaster damages according to hazard type when using county-level data. Perhaps unsurprisingly, hurricanes are the most damaging hazard in the data, followed by earthquakes. To compare with the cluster-level data, Table 2 displays similar information using cluster-level data. Droughts are the second-most damaging hazard type on average in the cluster-level data, as opposed to only the ninth most damaging in the county-level dataset. This is likely driven by the fact that in terms of the number of counties, droughts tend to be the largest clusters. This observation underscores the notion that the damage from hazards typically taking the form of spatial clusters affecting large numbers of counties may be especially understated when examining county-level data. Similar summary statistics by hazard type are shown for property and crop damage, as well as for spatiotemporal clusters in Tables IA.2, IA.3 and IA.4.

In this subsection, we have shown that there exist important differences between the distributions of county-level data and cluster-level data. In particular, cluster-level data exhibits greater positive skewness than county-level data, and larger clusters tend to have greater disaster damage. We also find evidence indicating that some disaster types appear more severe using cluster-level data than county-level data. In the next subsection, we will study whether counties that are part of larger clusters tend to experience greater disaster damage. We will do this by testing whether county-level disaster damage varies according to disaster damage experienced by other counties located in the same cluster.

2.2 Relationship Between County- and Cluster-Level Damage

Distributions using cluster-level data appear more skewed than when using county-level data, and climate events affecting more counties tend to yield higher damages. One potential explanation for this is that there could be "spillover effects" of disaster damage. In particular, it is possible that if a given county experiences a disaster at the same time that nearby counties face disasters, this could lead to worse economic outcomes. This could be due to strained resources to mitigate the damages, or greater degradation of shared infrastructure between the counties. It is also possible that these spillover effects may be especially problematic for certain hazard types. On the other hand, if nearby counties experience similar risks, this could lead them to share adaptation resources, which could result in improvements in preparations for disasters. In this subsection, we employ a regression analysis to test this hypothesis by examining whether counties belonging to clusters with greater disaster damage also tend to experience more damage.

One issue in examining how county-level damage relates to cluster-level damage is that disasters affecting more counties may mechanically have more damage. To address this concern, we calculate another version of the cluster-level damage in order to adjust for mechanical increases in cluster-level damage due to the increasing size of the cluster. Specifically, we calculated the median damage for any county experiencing a certain hazard type, conditional on nonzero damage. For each county, we sum up the median hazard damage for all hazards experienced by that county, and scale the total damage by this sum of median hazard damages:

$$\bar{D}_{i,t} = \frac{\sum_{h \in H(c_t^i)} D_{i,t,h}}{\sum_{h \in H_i} D_h^{median}}, \tag{1}$$

where $H(c_t^i)$ is the set of all hazards experienced by county i in time t, H_i is the set of all hazards experienced by county i throughout the entire sample period, $D_{i,t,h}$ is damages for hazard h experienced in county i at time t, and D_h^{median} is the median damages observed for hazard h. We refer to $\bar{D}_{i,t}$ as the rescaled damage for county i at time t. A similar measure can be calculated at the cluster level using the cluster-level damages. Accordingly, for each county, we calculate the rescaled cluster-level damage, for the cluster it is part of, while excluding the damage for the county of interest:

$$\begin{aligned} \bar{D}_{j,t}^{-i} &= \frac{\sum_{h \in H_{j,t}^{-i}} D_{j,t,h}}{\sum_{h \in H_j^{-i}} D_h^{median}}, \\ &= \frac{\sum_{h \in H_{j,t}} D_{j,t,h} - \sum_{h \in H_{i,t}} D_{i,t,h}}{\sum_{h \in H_j} D_h^{median} - \sum_{h \in H_i} D_h^{median}}, \end{aligned} \tag{2}$$

where $H_{j,t}$ is the set of all hazards experienced by cluster j at time t, and H_j is the set of all hazards experienced by cluster j throughout the entire sample period.

We then test the hypothesis that counties belonging to clusters with greater damage tend to experience more damage themselves by estimating the following regression:

$$log(\bar{D}_{i,t}) = \beta_1 log(\bar{D}^{-i}_{j,t}) + \Gamma X_{i,t} + \gamma_i + \tau_t + \epsilon_{i,t},$$

where $log(\bar{D}_{i,t})$ is the log of the rescaled damage of county i, at time t, $log(\bar{D}^{-i}_{j,t})$ is the log of the rescaled damage of cluster j (excluding damage for county i) at time t. $X_{c,t}$ are county-by-time controls. γ_i, τ_t are county and time level fixed effects. Specifically, to control for whether larger, or more populated areas, are more likely to experience severe disaster damage, we control for county GDP, population and wages. If counties tend to experience more damage when they are part of clusters that experience significant damage, we would expect that $\beta_1 > 0$.

Results for this regression are shown in column (1) of Table 3. β_1 is equal to about 0.45, meaning for that a 1% increase in cluster-level damage is associated with a 0.45% increase in county-level damage, indicating that counties belonging to larger clusters tend to experience greater disaster damage. This could potentially be consistent with spillover effects related to disaster damage.

We next explore whether there is heterogeneity in the relationship between county-level damages and cluster-level damages according to hazard type. In particular, the previous summary statistics showed that some hazard types appear more severe when analyzing them in cluster-level data. Similarly, do these spillover effects appear more severe for some hazard types than others? To test this hypothesis, we include hazard type indicator variables, and their interactions with the cluster-level disaster damages in columns (2) through (6). We explore damages related to droughts, heat, wildfires, floods and hurricanes. Unconditional on the amount of damage, all explored hazard types except for heat and hurricanes tend to be associated with more damage than the average disaster. Moreover, higher cluster-level damage is associated with more county-level damage for all five of the explored hazard types.[11] Overall, these results are consistent with a tendency for counties to experience

[11] Tables IA.5 and IA.6 show similar results using property and crop damages.

greater disaster damage when the rest of their cluster also experiences disaster damage, and with some hazard types appearing more severe when incorporating clustering into an analysis.

3 Implications of Clustering for Researchers

The analyses in this paper shed light on the value of accounting for clustering across space and time in handling data on natural disaster damages. Importantly though, while this paper only uses information on direct damages from natural disasters, problems related to clustering should be especially important in terms of the indirect effects of natural disasters. While it is outside the scope of the analysis in this paper, clustering may also be important for determining the difficulty of recovering from natural disasters. Additionally, while we examine county-level disaster damages, we expect that clustering could be important in any analysis of negative outcomes from natural disasters faced by individuals, firms or municipalities.

For this reason, the concept of natural disaster clustering does not necessarily call into question previous findings in the economics literature studying how county-level outcomes have changed in response to the direct effects of natural disasters. However, clustering of natural disaster damages may be important to consider in any case where spillover effects between counties may be important. In particular, if economic damages at the county level are correlated across space and time after experiencing damages from the same natural disaster damage cluster, effects of natural disasters on one county-month observation may spill over to another county-month observation. These spillover effects could transmit via shared aid resources or infrastructure, migration following disasters, or coordination by local governments in the recovery from the disaster and from investing in adaptation measures. Additionally, if these spillover effects have long-run ramifications, they could cause economic outcomes for different counties to remain correlated long after disasters occur.

The best way to approach these spillover effects in empirical work will differ based on the question being asked. Empirical analyses, such as those introduced in Berg et al. (2021), can be used to quantify these spillover effects. If the spillover effects appear significant, regression analysis can control for cluster-level co-variates in order to isolate county-level outcomes from the cluster-level outcome. In order to implement any approach of this sort, identifying clusters of natural disasters is necessary. For large natural disasters, data from the Federal Emergency Management Agency (FEMA) on emergency disaster declarations or billion dollar disasters can be used to identify natural disaster clusters, but this approach has two potential limitations. First, using FEMA emergency declarations will exclude counties that are affected by natural disasters, but not severely enough to have a disaster declared by FEMA. Second, using FEMA disaster declarations will exclude relatively smaller hazards that are not large enough to warrant attention from FEMA. To our knowledge, the only way to include these types of hazards and counties in an analysis using natural disaster clustering would be through using the methodology introduced in this paper.

4 Conclusion

It is clear that the temporal duration and the spatial footprint of natural disasters influence the intensity of damages that occur, and that damages from natural disasters tend to be spatially and temporally clustered. In this paper, we provide a tool allowing researchers to account for correlations in damages from natural disasters across counties and time. We find that accounting for clustering increases the skewness of the distribution of disaster damages. We also find that disaster damages in a particular county tend to be larger when the neighboring counties in its cluster experience greater disaster damage. Although causal inference regarding the effects of clustering on different economic outcomes is outside the scope of this paper, the analysis provides researchers with a useful tool to further study how natural disaster clustering can affect economic outcomes following disasters.

The implications of this paper will be especially important in any situation where disasters may have economically meaningful spillover effects. In this sense, accounting for clustering of natural disaster damages may help researchers to better account for second-order effects of natural disasters. The analyses in this paper could therefore lead to a richer understanding of how local economies are affected by disasters.

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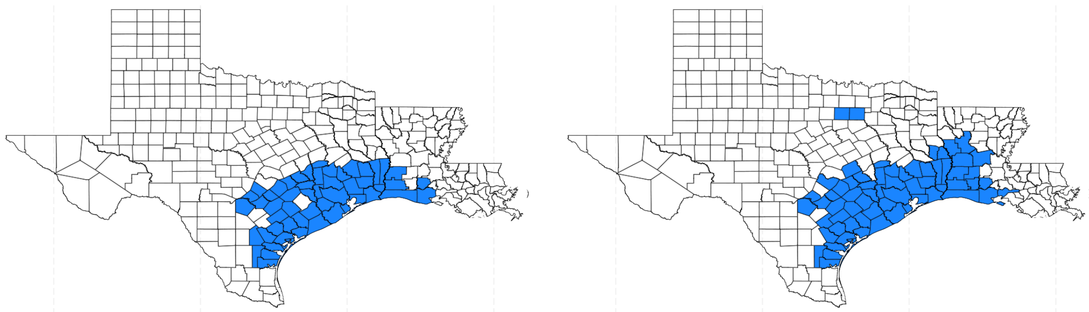
Figures

Figure 1: Clustering Output Example: Hurricane Harvey

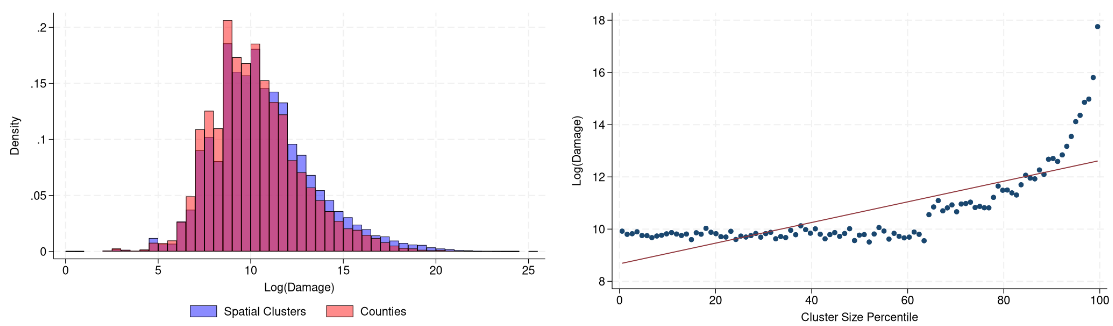
(a) Spatial Cluster (b) Presidential Disaster Declaration



Notes: This figure illustrates the set of counties that are included in the Harris County August 2017 spatial cluster as obtained in the procedure outlined in subsubsection 1.2.1 (left), and the set of counties included in the "Hurricane Harvey" Presidential Disaster Declaration (right).

Figure 2: Distributions of Damage Across Clusters

(a) Damage Histogram (b) Size vs Log(Damage)



Notes: This figure displays information on the distribution of damages across clusters. Panel (a) shows the distribution of the log of total damages defined at the cluster-level, alongside the distribution of the log of total damages defined at the county-level. Panel (b) shows the expected log damage conditional on the size of the cluster it lies in. Data on natural disasters are sourced from SHELDUS, and run from 2000 though 2020.

Tables

Table 1: Summary Statistics on Total Disaster Damages by Hazard – County-Level Data

	All Damage (thousands of $)						
	Count	Mean	SD	Median	90th Pct.	95th Pct.	99th Pct.
Hurricane	2,907	116,401.4	1,078,979.7	304.4	51,132.7	187,899.4	2,013,905.6
Earthquake	112	60,860.6	275,912.3	10,256.4	20,398.4	76,109.1	1,019,616.2
Heat	1,513	21,639.4	574,761.9	0.0	412.3	1,520.7	57,385.8
Coastal	1,539	21,458.9	481,718.2	0.0	222.0	1,517.0	23,487.4
Wildfire	2,280	18,542.7	233,944.5	85.9	4,349.4	13,983.5	285,734.3
Landslide	976	16,201.0	213,895.4	23.1	3,377.8	18,261.2	142,381.2
Tornado	11,847	11,807.7	327,615.9	140.0	3,166.9	9,929.7	108,074.9
Flooding	30,597	11,764.9	327,334.3	69.4	2,361.9	7,465.0	75,000.0
Drought	3,879	9,600.3	55,307.1	146.9	18,020.7	29,140.6	130,019.7
Lightning	9,861	4,370.6	103,756.7	38.5	627.9	1,568.6	22,275.0
Hail	13,174	4,299.6	81,688.3	57.7	1,866.3	6,447.5	54,917.8
Volcano	19	2,441.0	6,788.8	55.5	16,054.7	26,097.2	26,097.2
Tsunami	58	2,303.6	8,368.6	166.6	6,409.1	9,368.9	60,918.0
Winter	14,105	1,785.9	25,599.7	50.6	1,400.1	3,887.1	28,121.2
Wind	102,856	1,524.8	67,663.9	14.7	304.7	1,010.0	11,510.6
Thunderstorm	78,705	1,304.2	39,884.1	16.0	314.1	998.3	12,090.3
Fog	317	374.8	2,084.0	50.1	555.2	1,156.9	6,597.7
Avalanche	1,055	354.2	7,399.2	0.0	16.6	111.8	2,529.1

Notes: This table shows summary statistics of total damages from natural disasters by hazard-type, aggregated to the county level. Damage totals are in thousands of inflation-adjusted USD, and include property and crop damages. Damages data are sourced from SHELDUS, and run from 2000 through 2020.

Table 2: Summary Statistics on Total Disaster Damages by Hazard – Spatial Cluster-Level Data

	All Damage (thousands of $)						
	Count	Mean	SD	Median	90th Pct.	95th Pct.	99th Pct.
Hurricane	251	1,515,411.8	9,206,264.8	402.4	717,977.0	5,183,330.6	28,754,559.3
Drought	316	282,780.4	1,467,953.3	6,648.5	468,473.7	1,023,147.6	7,404,489.6
Earthquake	28	243,551.9	855,175.1	1,387.6	775,056.4	800,000.0	4,468,203.6
Heat	756	217,200.3	3,502,643.5	0.0	14,184.5	81,492.4	2,725,001.8
Landslide	548	191,678.5	1,657,752.1	63.1	33,485.2	193,630.8	4,468,203.6
Coastal	967	177,302.4	3,219,685.8	0.0	4,499.4	28,905.7	1,168,300.2
Tornado	4,443	95,185.1	2,154,472.4	217.1	19,371.8	76,109.1	947,638.0
Wildfire	1,061	65,565.3	644,749.1	256.4	24,307.3	94,620.1	1,624,240.5
Flooding	7,836	64,262.7	1,674,410.3	87.4	9,133.1	38,130.5	479,159.0
Hail	4,359	58,071.9	1,579,582.4	103.7	18,369.7	74,124.2	617,133.1
Lightning	5,684	55,398.8	1,465,435.3	54.2	5,016.8	29,528.4	468,473.7
Thunderstorm	15,783	30,499.4	1,166,570.8	26.8	1,783.0	8,963.9	194,103.9
Avalanche	333	29,874.3	410,041.4	0.0	998.8	11,759.7	230,797.9
Fog	158	28,271.8	165,974.5	126.4	13,243.5	98,944.2	870,080.4
Wind	19,136	25,842.4	1,059,512.1	24.0	1,509.5	7,407.6	169,508.6
Tsunami	32	21,282.6	37,244.0	2,451.9	93,238.3	123,556.2	126,338.0
Winter	2,227	19,724.0	204,289.9	61.1	10,131.0	41,626.6	395,161.7
Volcano	11	4,216.2	8,645.4	444.0	16,054.7	26,097.2	26,097.2
	Cluster Size (# of Counties)						
Tsunami	32	44.7	77.6	3.5	189.0	233.0	270.0
Drought	316	29.7	88.5	6.5	55.0	89.0	368.0
Hurricane	251	24.0	63.8	2.0	47.0	171.0	309.0
Heat	756	19.8	76.2	1.0	33.0	99.0	380.0
Landslide	548	18.2	66.8	1.0	27.0	55.0	384.0
Tornado	4,443	14.9	53.1	1.0	30.0	71.0	242.0
Hail	4,359	14.4	52.1	1.0	30.0	62.0	240.0
Fog	158	13.4	74.0	2.0	20.0	39.0	90.0
Coastal	967	13.3	67.2	1.0	13.0	46.0	309.0
Avalanche	333	12.4	76.9	3.0	11.0	17.0	240.0
Winter	2,227	12.3	39.9	2.0	31.0	52.0	173.0
Lightning	5,684	11.8	46.9	1.0	22.0	53.0	216.0
Flooding	7,836	11.1	41.4	1.0	23.0	47.0	185.0
Wildfire	1,061	11.0	56.2	1.0	18.0	34.0	208.0
Thunderstorm	15,783	7.0	29.8	1.0	11.0	26.0	106.0
Wind	19,136	6.6	27.4	1.0	11.0	24.0	91.0
Earthquake	28	4.2	14.5	1.0	4.0	9.0	78.0
Volcano	11	1.7	2.1	1.0	2.0	8.0	8.0

Notes: This table shows summary statistics of damages and cluster sizes from natural disasters by hazard-type, aggregated to the spatial cluster level. Damage totals are in thousands of inflation-adjusted USD, and include property and crop damages. Damages data are sourced from SHELDUS, and run from 2000 through 2020.

Table 3: Differences in Total Damages According to Hazard Type

	$\bar{D}_{i,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
Drought		0.319**				
		(0.129)				
Drought × $\bar{D}_{j,t}^{-i}$		0.299***				
		(0.070)				
Heat			-0.531***			
			(0.124)			
Heat × $\bar{D}_{j,t}^{-i}$			0.183**			
			(0.082)			
Wildfire				0.264***		
				(0.088)		
Wildfire × $\bar{D}_{j,t}^{-i}$				0.200***		
				(0.042)		
Flooding					0.239***	
					(0.031)	
Flooding × $\bar{D}_{j,t}^{-i}$					0.142***	
					(0.021)	
Hurricane						-0.594***
						(0.177)
Hurricane × $\bar{D}_{j,t}^{-i}$						0.147***
						(0.041)
$\bar{D}_{j,t}^{-i}$	0.445***	0.428***	0.444***	0.441***	0.405***	0.440***
	(0.013)	(0.012)	(0.013)	(0.013)	(0.016)	(0.014)
Log GDP	-0.018	-0.012	-0.016	-0.016	-0.019	-0.022
	(0.073)	(0.071)	(0.073)	(0.074)	(0.074)	(0.074)
Average Wages	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log Population	-0.054	-0.081	-0.049	-0.070	-0.083	-0.054
	(0.219)	(0.213)	(0.220)	(0.219)	(0.223)	(0.219)
Constant	0.005	0.228	-0.064	0.146	0.281	0.087
	(2.169)	(2.147)	(2.172)	(2.155)	(2.169)	(2.162)
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	115,712	115,712	115,712	115,712	115,712	115,712
R^2	0.339	0.344	0.339	0.340	0.347	0.339

Notes: This table shows the results of a regression of log of total damages for both county-level aggregates on indicators for the presence of a hazard in a given county/cluster along with an interaction of the damage indicator with the log of damage of that county's spatial cluster excluding that county. Damages are aggregated to the county/cluster level, and are in inflation-adjusted USD. Damages data are sourced from SHELDUS, and run from 2000 through 2020. Standard errors are double-clustered at the county- and month-level. *, **, and *** indicate 10%, 5%, and 1% significance, respectively.

Internet Appendix

IA.A Economics Literature

This internet appendix contains a broad review of the literature on natural disasters in finance and economics.[IA.1] Many of these studies take the form of panel regressions using data aggregated at the county-by-period (e.g., month, quarter, year) level, while others isolate a single natural disaster event (e.g., Hurricane Katrina) and examine how geographic variation in exposure to that event is linked to economic outcomes. Researchers tend to agree that natural disasters have broadly negative consequences for households in the short term. However, the results vary significantly according to demographic characteristics, and are more mixed over the long run. Much of the research on natural disasters has focused on hurricanes since they tend to be disproportionately damaging.

IA.A.1 Natural Disasters and Household Credit

It is natural to expect that natural disasters could affect household credit outcomes. On the one hand, damages from natural disasters could lead households to demand more credit. At the same time, disasters may lead to income shocks, inhibiting the ability of borrowers to repay debt. Several papers attempt to understand the overall effect of disasters on household borrowing. Numerous papers have investigated a specific natural disaster event in order to understand the impacts of natural disaster exposure on households.

Several papers examine how Hurricane Katrina affected households. For instance, Gallagher and Hartley (2017) show that in the short run, more severe flooding from Hurricane Katrina was associated with temporary increases in credit card debt and debt delinquencies, as well as temporary drops in credit scores. On the other hand, they also show that in the long run, flooding led to decreases in total debt, which the authors attribute to the use of flood insurance payouts to pay down mortgage debt. Furthermore, they find that two years after the event, non-local lenders tend to exit the market, while local lenders tend to recover to pre-Katrina levels of lending. In a subsequent analysis, Bleemer and van der Klaauw (2019) find that a decade after Hurricane Katrina, homeownership and credit insolvency rates in flooded neighborhoods remain persistently lower than in non-flooded neighborhoods. However, they find that residents in the surrounding region were better off on net, as indicated by higher rates of consumption and homeownership, lower levels of debt, and lower rates of bankruptcy and foreclosure. They find that these effects tend to favor younger and low-income residents.

Researchers found similar effects when studying Hurricane Harvey. Billings et al. (2022) use variation in flooding from Hurricane Harvey to understand the impacts of flood losses on household credit. They find that credit-constrained homeowners in flooded areas experienced significant increases in bankruptcies and delinquencies relative to those not in flooded areas, but that flood insurance ameliorated these effects. In a follow-up paper, Gallagher et al. (2023) find that for college-aged adults, the likelihood of having student debt is reduced in

[IA.1] See Botzen et al. (2019) for another useful review of the economics literature on natural disasters.

areas that experienced flooding compared to areas that did not, and that local university enrollment appears to drop in the Texas counties that were more affected by hurricane damage. The authors propose that households experiencing flooding are less able to secure credit for additional schooling, causing them to opt out of human capital investments.

IA.A.2 Effects of Disasters on Financial Assets and Banks

Beyond the household effects, there is a literature examining the effects of natural disasters on local firms and asset prices. The literature finds evidence that firms are negatively affected by natural disasters, and this is reflected in financial markets. Collier et al. (2024) find, using a sample of credit reports and FEMA flooding estimates data, that in the aftermath of Hurricane Harvey, business credit delinquencies doubled in areas exposed to more flooding damage, and that these effects are driven by independent businesses. Kruttli et al. (2023) find that the implied volatility of stock options of firms increased in advance of hurricanes affecting regions the firm has a presence in. Comparing the implied volatility to the eventual realized volatility indicates that investors underreact, although estimates of this underreaction have decreased following Hurricane Sandy.

While natural disasters have been shown to affect financial markets, the effects are less clear for banks. Correa et al. (2022) show that corporate loan spreads for borrowers located in areas at high risk of experiencing a hurricane increase following hurricanes in other regions. This could indicate that lenders incorporate beliefs about the likelihood and severity of hurricanes in loan pricing. On the other hand, Blickle et al. (2021) find that banks are not significantly impacted by disasters. They find, using a county-level analysis, that disasters increase the demand for loans, offsetting losses and increasing profits at larger banks, while local banks seem to avoid lending in areas in which flooding is more common than official estimates. This finding is consistent with the idea that local firms can make use of local knowledge to more efficiently account for natural disaster risk. Similarly, Koetter et al. (2020) show that local German banks lend to firms affected by flooding and Berg and Schrader (2012) show that relationships between banks and borrowers can mitigate reductions in access to credit after volcanic eruptions in Ecuador.

IA.A.3 Disasters and Housing, Mortgage, and Insurance Markets

Given that natural disasters can adversely affect household credit, it is important to understand how they affect housing markets, as well as mortgage and insurance markets. This subsection discusses effects of natural disasters on these markets, and how they can affect households' location decisions.

Several papers use FEMA flood map data to show that government mandates to purchase homeowner insurance can reduce borrower access to credit. These flood maps are particularly useful as lags in updates to the flood maps provide researchers an opportunity for identification. Sastry (2021) uses highly granular data on flood maps, home- and loan-level mortgage data, and data on insurance coverage and construction costs. Using an estimation strategy relying on the fact that government-backed flood insurance has a strict limit, they find that insurers offload flood risk both to the government through subsidized policies and to borrowers through requirements of higher down payments. They also show that updates to flood maps lead banks to reduce loan-to-value ratios while interest rates remain roughly the same. Blickle and Santos (2022) use Home Mortgage Disclosure Act (HMDA) data along with FEMA flood map data to investigate how banks adjust lending in response to levels of and changes to insurance requirements. They find that banks are less willing to lend in areas after flood maps are extended. They also find that local banks are less responsive to updates to flood zone maps, suggesting that they use local knowledge to more responsively monitor true risk exposure relative to the insurance requirements. These results suggest that mandatory insurance standards may unintentionally harm low-income and low-credit borrowers.

It is not clear that insurers will continue to be willing to bear this risk. Issler et al. (2021) combine a game theoretic framework with closely matched data on fire burn areas to consider how wildfires affect housing and mortgage markets in California. Consistent with the model predictions, they find that insurance payouts cause increases in square footage and decreases in mortgage terminations in the aftermath of a fire, suggesting that insurance payouts lead to a general improvement in the value of homes. They further argue that perverse incentives to improve homes in high fire-risk areas may jeopardize the ability of insurance companies to bear the risks in the absence of the ability to raise prices. Sastry et al. (2023) use county- and zip code-level data on insurance to construct a comprehensive picture of how insurers respond to increases in hurricanes in Florida. They find that traditional insurers exit following increases in natural disasters. This leads to the entry of riskier insurers, who offload the risk to both the government and mortgage lenders.

The exit of insurers is especially troubling as households are likely to demand more insurance as disaster-risk increases. Gallagher (2014) uses a community-level dataset with information on presidential disaster declarations to understand how affected households respond to flooding in their communities and unaffected households respond to flooding in other communities in their television media markets. Flooded households have a sharp spike in sign-ups for flood insurance and unaffected households in flooded media markets have a significant, though smaller increase in sign-ups. These findings indicate that households respond to information about floods by purchasing insurance. Similarly, theoretical research argues that household location decisions and home values are driven by a combination of households' beliefs about the level of flood risk and their preferences for waterfront living (Bakkensen and Barrage, 2018).

IA.A.4 Macroeconomic Effects of Natural Disasters

Intuitively, one would expect natural disasters to be a negative local shock to local economies, and there is some literature supporting this conjecture. Deryugina (2017) finds that local government expenditures appear to increase significantly in the decade of a hurricane. They also find that on average, disaster aid is not sufficient to cover the present value of natural disasters, although victims appear to be better insured than previously thought. Jerch et al. (2023) similarly find that hurricanes reduce city- and county-level government tax revenues in the following decade. They also find that hurricanes raise municipal bond default risk, leading to ratings downgrades, further increasing municipal costs of capital. Similarly, Auh et al. (2022) show that natural disasters reduce returns of uninsured municipal bonds in the weeks following a disaster. The authors also find heterogeneities in this effect according to disaster severity, federal aid, and local economic conditions. Similarly, Acharya et al. (2022) find that municipal bond pricing is affected by heat stress.

Nonetheless, it is not always the case that natural disasters are a net drag on the economy, because the negative economic consequences from disasters may be offset by disaster aid and private insurance payouts. Using county-level disaster declarations data from FEMA, Tran et al. (2020) find that total and per-capita income increase in the 8 years following natural disasters, with a temporary local employment boost followed by a long-term increase in wages. This effect appears to be increasing in the size of the disaster. Additionally, house prices tend to increase while population remains roughly constant, particularly in areas with inelastic housing supply. Similarly, Deryugina et al. (2018) find that households exposed to Katrina appear to experience transitory reductions in income, while they actually increase their incomes over the longer term. This increase in income is especially concentrated among movers out of New Orleans. This finding on mobility is consistent with Boustan et al. (2020), which show that severe disasters increase out-migration, although unlike Tran et al. (2020), these authors find housing costs and income growth decreased in the decade after disasters. In contrast, Kim et al. (2022) find that severe weather shocks are associated with persistent reductions in aggregate industrial production growth, and increases in unemployment and inflation.

Researchers have also examined macroeconomic effects of disasters at the country level. Skidmore and Toya (2002) find that exposure to repeated climate disasters leads to a substitution of physical capital investment towards human capital investment, while also prompting a more frequent updating of the capital stock. Surprisingly then, higher frequency of natural disasters can boost total factor productivity. Cavallo et al. (2013) provide one explanation for the boost in total factor productivity by showing that while very large natural disasters reduce output, small disasters do not affect economic growth. These effects disappear, however, when controlling for major negative political events in the wake of these disasters. Bakkensen and Barrage (2018) also show that cyclone risk is largest for small island nations, and otherwise is only modestly underestimated.

Overall, the economics literature finds mixed evidence on the economic consequences of natural disasters. While several papers show evidence consistent with negative effects of disasters on the economy, there is also significant work showing no strong effect, and even some work showing a positive effect. Of course, these findings are typically based on analyses from panel data, which requires an assumption that that natural disaster risk in one location is uncorrelated with natural disaster risk in another location. In the next section, we will review the climate science literature on natural disasters, which will allow us to interrogate whether this assumption is consistent with the realities observed by the scientific community.

IA.B Climate Science Literature

In this Internet Appendix section, we describe the scientific literature related to climate change. There is an extensive climate literature relating to the societal impacts of natural disasters which aims to understand the mechanisms and impacts of natural disasters historically, as well as to model future natural disasters and their impacts on society.

IA.B.1 Distributions of Severe Disasters Across Time and Space

A large strand of the climate literature has been devoted to understanding the spatial and temporal distributions of natural disaster damages. Much of these papers provide evidence that natural disasters are spatially and temporally linked, and can amplify the effects of subsequent disasters in nonlinear ways. One of the first papers to consider the spatial and temporal correlation between disasters was Wheater et al. (2005), which critiques methods that model individual rainstorms as discrete events. They propose that a methodology using more temporally and spatially continuous measures would provide better estimates of the true geographic distribution of flood risks.

A substantial body of literature also aims to understand the determinants of flood risk, and broadly shows that damage from flooding is conditional on local infrastructure, previous weather conditions, and the climate of nearby regions. Li et al. (2016) find when looking in Africa, that several factors determine how destructive and deadly a storm will be, conditional on the severity of rainfall. In particular, higher levels of forest coverage, as well as lower levels of urbanization and economic development were associated with an increase in the frequency of catastrophic flooding events. Fu et al. (2023) find that there have historically been significant heterogeneities in the levels and seasonality of flood risk across China, and over time. They show that the simultaneous increases in the frequency and severity of both drought and rainfall are linked via the same large-scale climate factors.

Janizadeh et al. (2021) model future flood risks in northwestern Iran using ensemble machine learning models. They find that granular data about geography (e.g., elevation, slope and proximity to rivers) as well as precipitation is important for predicting flood risk. More broadly, Merz et al. (2021) find that the rate of disastrous flooding has increased in severity with population and economic growth, as well as the frequency of severe storms. However, they suggest that the increase in the severity of storms is often partially offset by more effective flood mitigation and adaptation strategies. They suggest that, over the longer term, unanticipated floods due to anomalous atmospheric conditions interacting with an ill-equipped built environment are likely to be the largest source of damage and fatalities.

IA.B.2 Compound Events and Their Societal Effects

In the previous subsection, we discussed how disasters tend to be correlated across space and time. We now explore how the effects of different hazard types may be correlated. There is a significant literature studying how the co-occurrence of natural disasters can lead to "compound effects," where the downstream consequences of multiple disasters are greater than the sum of their parts. This could occur because experiencing multiple disasters could strain natural and institutional systems, leading them to breakdown. Much of the work relating to compound effects has been theoretical. Leonard et al. (2014) propose a framework for considering the risks and consequences of natural disasters, which rejects the conventional approach that natural disaster risks from multiple hazard types are independently distributed. They suggest that the causes of seemingly disparate hazard types are linked, which would lead compound events to be more frequent and more destructive than under existing models. The authors note that natural disasters can have long-term effects on a region's climate or conditions that can compound the effects of future disasters.[IA.2] Similarly, natural disasters can alter conditions in regions far away from where the disaster actually occurs.

In a later paper, Zscheischler et al. (2018) argue that it is important to model different hazard types as being driven by different factors. Subsequently, Zscheischler et al. (2020) identify broad categories of natural disaster compounding, including temporal compounding (i.e., multiple hazards occurring in succession) and spatial compounding (i.e., hazards in multiple connected locations). These hazards may be driven by a related cause, which can lead to greater damage. Moreover, destructive natural feedback loops and the failure of important infrastructure can result from hazards occurring nearby each other.

Some researchers have focused specifically on the compounding effects driving flooding. Wahl et al. (2015) demonstrate that the combination of tidal surge and heavy rain is especially likely to lead to coastal flooding. They also find that the risk of both tidal surge and heavy rain is especially severe on the US Atlantic/Gulf coast, and that the risk of these hazards has increased in recent years. In another investigation of flooding as an outcome of other compound events, Lian et al. (2013) find that upstream rainfall can strain water drainage systems, leading to unanticipated flooding from high tides. Zhang et al. (2018) investigate the meteorological phenomena surrounding Hurricane Harvey, and show that urbanization exacerbated both the severity of rainfall as well as the flood risk, and that these effects combined to amplify the severity of the flooding.

IA.B.3 Future Projections of Climate Disasters

The previous subsections reviewed literature on correlations between the effects of disaster damage across space, time and hazard type. This subsection will review how scientists expect natural disaster risks to evolve in the future. Much of the literature attempts to understand how the evolution of climate change could affect realizations of natural disaster risk. These papers consider a variety of global temperature rise scenarios, incorporating knowledge on the compound effects of natural disasters.

Woodruff et al. (2013) show that under the expected rates of sea level rise, the severity of hurricanes is expected to increase, even holding constant the frequency of hurricanes. They suggest that changes in land use may ameliorate these increases, and that geography is a crucial determinant of the level of property loss given a particular event. Marsooli et al. (2019) find, modeling the trajectory of hurricane risks under anticipated sea level rise, that the compound effects of these hazards together would cause 100-year flooding to occur

[IA.2] Lange et al. (2020) also provide evidence that the frequency of compound hazards has increased as global average temperatures have risen.

annually in the Atlantic and Gulf cost regions. Lin et al. (2012) use a general circulation model (GCM) in combination with a hydrodynamic model to simulate possible surge events under different projections of climate change. They show that due to increased surge events, 100-year floods are likely to occur between 1-in-3 and 1-in-20 years by the late 2020s.

Work has also been done to understand the likelihood of the co-occurrence of extreme temperature and drought events. Ridder et al. (2022) model future changes to the spatial correlations of heatwaves and drought as well as extreme winds and precipitation. Their models suggest that these compound events will occur more frequently under all emissions scenarios, with substantial regional heterogeneity. Further examining heat-drought, Bevacqua et al. (2022) use ensemble climate models to predict the future co-occurrence of hot-dry events. Their models seem to suggest that precipitation is the main driver of the occurrence of hot-dry events because the conditional probability of at least moderate heat given drought becomes extremely high with even 2°C of warming.

On a broader level, researchers have tried to use some of the relationships between existing disaster types in order to assess the types of disaster risk increases that would be most damaging to society. Sarhadi et al. (2018) simulate the likelihood of spatial and temporal co-occurrence of natural disasters in an attempt to understand the downstream effects of a nonstationary climate, and find that climate change is likely to double the joint probability of the co-occurence of heat and dought in the same region, and broadly that it will increase the likelihood of the simultaneous co-occurrence of these stresses in multiple regions simultaneously. Zhou et al. (2023) model the future statistical dependence of temperature and precipitation extremes, and demonstrates a significant spatial correlation of these extreme events. According to their model, there is likely to be a significant increase in the simultaneous occurrence of extreme drought and flooding events that, together, will make adaptation to climate change more costly and difficult. Their findings suggest that the concurrent nature of extreme precipitation and temperature events poses substantial risks to natural ecosystems' abilities to self-regulate and act as a carbon sink, further amplifying climate change. They argue that "although future risks of climate extremes vary geographically, they are becoming more strongly interlinked through further warming with increased climate variability and spatial dependence of climate extremes." Anticipating and modeling the ways in which future disaster risks are likely to increase under plausible climate change scenarios is very important because of the threats these hazards can pose towards human society.

IA.B.4 Projected Societal Implications of Increasingly Severe Disasters

Future changes in the probabilities of extreme natural disasters are expected to have serious socioeconomic effects. Climate change is likely to threaten the reliability of the energy grid, and the spatial correlation of temperature shocks appear to be a key driver of this. Do et al. (2023) analyze power outages in the United States between 2018 and 2020 and find that outages are pervasive and widespread across the country, and that the most severe outages frequently co-occur with severe weather events. Counties within 100 miles of a tropical cyclone appear to be the most prone to power outages relative to other severe weather incidents, suggesting that natural disasters can have consequences outside of the places they most directly impact. Perera et al. (2020) model the impacts of a potential increase in the frequency of extreme heat and cold on the energy system in Sweden. They find that these extreme weather demands will lead to shocks both to energy demand and energy supply. Because of the spatial correlation of these weather shocks, strain on the entire energy system is likely to increase. Stone Jr et al. (2021) examine the potential for electrical grid failure under extreme heat events in the United States. They find that in recent years, power grid blackouts have increased in frequency as simultaneous heatwaves in multiple regions have placed unanticipated strain on energy systems. Under modeled heatwave scenarios, their findings suggest that spatial compounding is likely to play a significant role in triggering a rise in the frequency of widespread blackouts. Ultimately, their findings suggest that a much greater share of the urban population is likely to face an elevated risk of heat exhaustion and heat stroke relative to the present.

Climate change can also threaten food production systems due to both heat and drought events. Tigchelaar et al. (2018) argue corn production will likely be adversely affected by increased global frequencies of heat-drought events. Their research suggests that, absent technological change enabling the growth of corn under higher heat scenarios, major disruptions in the global supply of corn would become a regular occurrence under a 4°C warming scenario, with especially severe consequences for low- and middle-income countries. Thiery et al. (2021) take a more holistic approach, investigating how many extreme events the average person in a given generation will expect to experience over their lifetime. They find that expected lifetime exposure to heat waves, crop failures, droughts, and river flooding has increased significantly for current birth cohorts (those born after 2020). However, they note that the degree of these increases is highly sensitive to the degree of warming, and suggest that failing to take into account compounding effects may lead to underestimating the true increase in severe disaster risk.

Many models of future climate risks aim to understand the potential threat of multiple simultaneous shocks to key economic systems. Climate change is expected to compromise the reliability of energy grids, with spatially correlated temperature extremes increasing both energy demand and supply challenges. Additionally, the compounding effects of heat and drought are likely to significantly impact food production, such as for crops like corn, with potential disruptions becoming more common under higher warming scenarios. Ultimately, the cumulative effects of extreme climate events, amplified by compounding effects, are expected to increase significantly for future generations.

IA.C Additional Tables and Figures

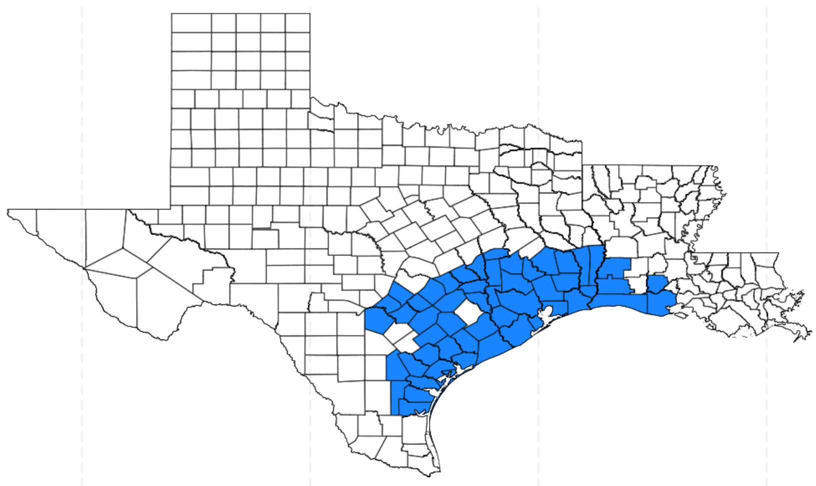
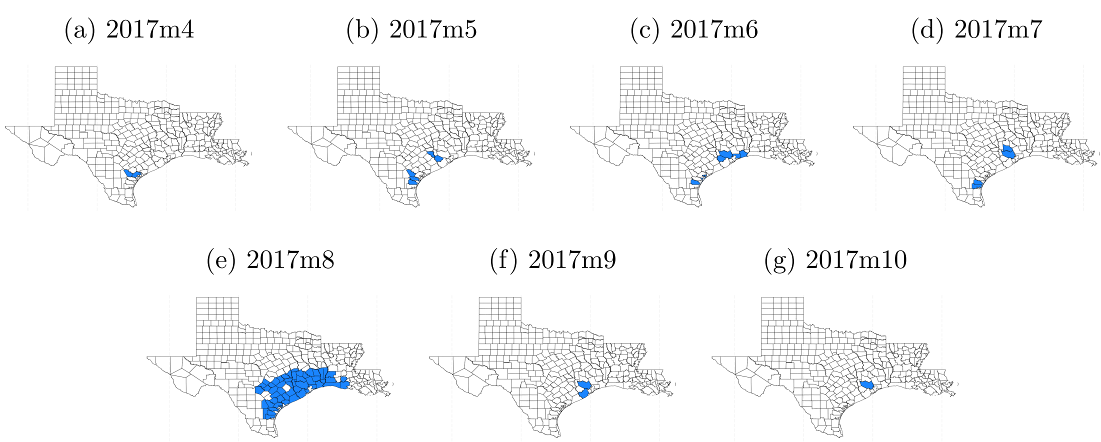


Figure IA.1: Spatiotemporal Cluster Containing Harris County, April-October 2017

This figure illustrates the entire set of counties that are included in the Harris County April-October 2017 spatiotemporal cluster, obtained following the process outlined in subsubsection 1.2.2.

Figure IA.2: Temporal Evolution of Harris County Spatiotemporal Cluster, 04-10/2017

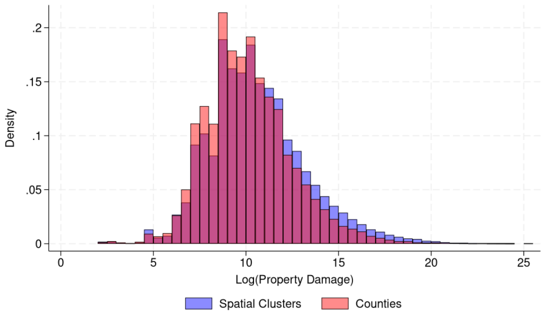


(a) 2017m4 (b) 2017m5 (c) 2017m6 (d) 2017m7

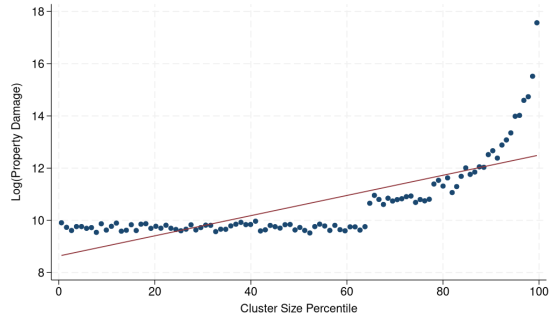
(e) 2017m8 (f) 2017m9 (g) 2017m10

Figure IA.3: Distribution of Property Damage Across Spatial Clusters

(a) Property Damage Histogram



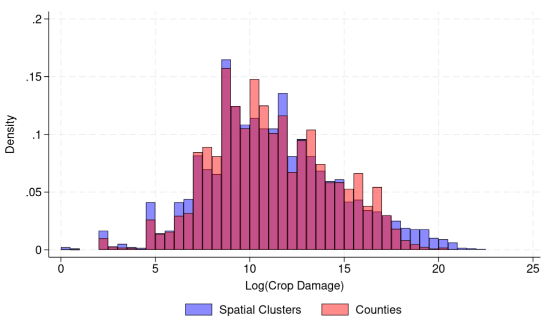
(b) Size vs Log(Property Damage)



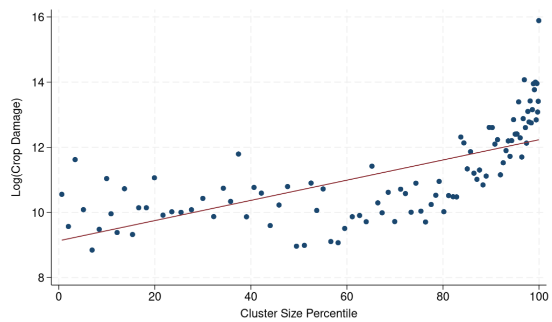
Notes: Panel (a) compares the distributions of the log of property damages, based on whether they are aggregated to the county level or to the spatial cluster level, following the process outlined in subsubsection 1.2.1. Panel (b) shows the expected log property damages conditional on the size of the spatiotemporal cluster it lies in. Data on natural disasters are sourced from SHELDUS, and run from 2000 though 2020.

Figure IA.4: Distribution of Crop Damage Across Spatial Clusters

(a) Crop Damage Histogram



(b) Size vs Log(Crop Damage)

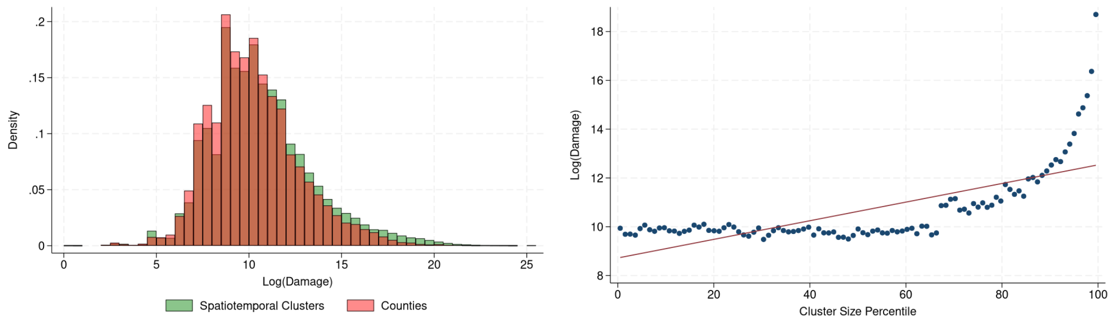


Notes: Panel (a) compares the distributions of the log of crop damages, based on whether they are aggregated to the county level or to the spatial cluster level, following the process outlined in subsubsection 1.2.2. Panel (b) shows the expected log crop damages conditional on the size of the spatiotemporal cluster it lies in. Data on natural disasters are sourced from SHELDUS, and run from 2000 though 2020.

Figure IA.5: Distribution of Total Damage Across Spatiotemporal Clusters

(a) Damage Histogram

(b) Size vs Log(Damage)



Notes: Panel (a) compares the distributions of the log of total damages, based on whether they are aggregated to the county level or to the spatiotemporal cluster level, following the process outlined in subsubsection 1.2.1. Panel (b) shows the expected log total damage conditional on the size of the spatiotemporal cluster it lies in. Data on natural disasters are sourced from SHELDUS, and run from 2000 though 2020.

Table IA.1: Summary Statistics

	Counties						
	Count	Mean	SD	Median	90th Pct.	95th Pct.	99th Pct.
Property Damage	161,664	3,613.9	154,580.5	15.8	450.6	1,425.3	18,249.3
Crop Damage	161,664	413.8	9,368.8	0.0	0.0	51.4	6,320.9
Total Damage	161,664	4,027.6	155,071.3	19.5	666.0	2,455.1	28,129.6
Injuries	161,664	0.3	6.8	0.0	0.0	1.0	5.0
Fatalities	161,664	0.1	1.8	0.0	0.0	0.0	1.0
Size	161,664	1.0	0.0	1.0	1.0	1.0	1.0
GDP	149,031	8,495.4	27,857.5	1,369.3	18,730.0	41,368.7	109,829.3
Population	159,101	158,076.2	416,648.7	40,234.0	371,839.0	748,626.0	1,975,076.0
Wages	149,416	3,237.9	2,352.2	2,792.8	5,387.5	6,556.6	9,859.4
	Spatial Clusters						
Property Damage	37,296	15,664.7	765,883.9	21.9	1,032.6	4,144.2	74,840.0
Crop Damage	37,296	1,793.5	44,856.2	0.0	0.0	40.5	7,990.4
Total Damage	37,296	17,458.2	777,418.7	23.6	1,230.1	5,555.8	116,869.9
Injuries	37,296	1.5	25.8	0.0	1.0	3.0	23.0
Fatalities	37,296	0.3	6.0	0.0	1.0	1.0	5.0
Size	37,296	4.3	20.0	1.0	6.0	13.0	58.0
GDP	34,380	32,175.4	115,593.6	3,040.0	65,681.8	149,291.7	510,954.1
Population	36,712	643,224.6	2,388,171.1	79,821.5	1,236,064.0	2,869,672.0	9,996,678.0
Wages	34,753	3,550.8	2,103.3	3,186.9	5,731.4	6,768.5	9,436.6

Notes: This table shows summary statistics of the fatalities, injuries, property damage, crop damage, and total (property and crop) damage from natural disasters, aggregated to the county- and spatial cluster-levels, as well as the average GDP, population, size, and wages in each of these units of aggregation. GDP totals are annual, and in millions of USD. Wage totals are quarterly per-capita. Population figures are annual. Damage totals are in thousands of inflation-adjusted USD, and include property and crop damages. Damages, injuries, and fatalities data are sourced from SHELDUS, and run from 2000 through 2020. GDP data are sourced from the Bureau of Economic Analysis. Population data are sourced from the US Census Bureau's Annual Community Survey (ACS). Wages data are sourced from the Quarterly Census of Employment and Wages (QCEW).

Table IA.2: Summary Statistics on Property and Crop Damage by Hazard – County-Level Data

	Property Damage (thousands of $)						
	Count	Mean	SD	Median	90th Pct.	95th Pct.	99th Pct.
Hurricane	2,907	112,289.2	1,077,798.3	250.0	38,958.3	152,580.2	2,013,503.0
Earthquake	112	60,860.6	275,912.3	10,256.4	20,398.4	76,109.1	1,019,616.2
Coastal	1,539	21,328.7	481,720.0	0.0	181.2	1,105.2	21,839.3
Heat	1,513	21,048.3	574,728.6	0.0	263.6	891.1	7,663.8
Wildfire	2,280	17,486.0	232,077.7	71.7	3,918.6	12,004.1	167,726.4
Landslide	976	16,027.6	213,651.8	22.3	3,222.1	17,673.4	142,381.2
Tornado	11,847	11,393.6	327,218.8	132.7	2,764.8	8,444.6	100,010.0
Flooding	30,597	11,279.9	327,081.6	61.1	1,822.5	5,689.9	64,808.0
Lightning	9,861	4,176.0	102,742.3	37.0	585.6	1,404.0	16,584.0
Hail	13,174	3,699.5	81,315.2	36.4	890.5	3,019.8	50,086.5
Tsunami	58	2,272.5	8,345.2	166.6	6,409.1	8,739.7	60,918.0
Drought	3,879	1,650.0	25,061.3	0.0	153.8	742.6	18,035.0
Wind	102,856	1,330.7	67,297.1	14.1	260.0	740.0	7,548.2
Winter	14,105	1,233.8	23,502.2	38.1	765.5	2,250.4	20,770.5
Thunderstorm	78,705	1,124.3	39,481.4	15.2	261.0	712.3	7,400.3
Volcano	19	888.1	3,672.9	55.5	148.0	16,054.7	16,054.7
Fog	317	355.6	2,057.4	49.4	527.8	1,118.3	4,792.8
Avalanche	1,055	353.9	7,399.2	0.0	15.3	101.1	2,529.1
	Crop Damage (thousands of $)						
Drought	3,879	7,950.3	47,015.1	53.6	16,813.5	28,144.6	80,528.3
Hurricane	2,907	4,112.2	27,523.2	0.0	805.3	20,877.1	98,255.6
Volcano	19	1,552.8	5,958.6	0.0	1,221.8	26,096.4	26,096.4
Wildfire	2,280	1,056.7	28,018.1	0.0	6.4	64.6	10,930.4
Hail	13,174	600.0	5,852.0	0.0	284.9	1,165.3	15,670.2
Heat	1,513	591.2	7,613.5	0.0	0.0	58.3	4,661.2
Winter	14,105	552.1	10,092.5	0.0	0.0	114.2	7,585.1
Flooding	30,597	485.0	7,629.4	0.0	21.5	291.3	10,267.4
Tornado	11,847	414.0	8,837.4	0.0	12.0	159.6	3,653.6
Lightning	9,861	194.6	4,272.9	0.0	0.0	1.1	728.5
Wind	102,856	194.1	6,049.6	0.0	0.0	6.1	1,221.8
Thunderstorm	78,705	179.8	4,449.4	0.0	0.0	12.2	1,460.9
Landslide	976	173.3	2,023.8	0.0	0.0	11.1	8,668.0
Coastal	1,539	130.1	1,787.8	0.0	0.0	0.0	534.2
Tsunami	58	31.1	237.2	0.0	0.0	0.0	1,806.2
Fog	317	19.2	214.8	0.0	0.0	5.7	177.6
Avalanche	1,055	0.3	6.6	0.0	0.0	0.0	0.0
Earthquake	112	0.0	0.0	0.0	0.0	0.0	0.0

Notes: This table shows summary statistics of property and crop damage from natural disasters by disaster-type, aggregated to the county level. All Damage totals are in thousands of inflation-adjusted USD, and include property and crop damages. Damages data are sourced from SHELDUS, and run from 2000 through 2020.

Table IA.3: Summary Statistics on Property and Crop Damage by Hazard – Spatial Cluster-Level Data

	Property Damage (thousands of $)						
	Count	Mean	SD	Median	90th Pct.	95th Pct.	99th Pct.
Hurricane	251	1,462,571.6	9,084,690.0	394.5	522,450.1	4,801,737.6	28,750,380.8
Earthquake	28	243,551.9	855,175.1	1,387.6	775,056.4	800,000.0	4,468,203.6
Heat	756	202,426.9	3,493,693.1	0.0	11,140.8	47,055.8	2,585,458.1
Drought	316	180,844.7	1,394,458.6	78.1	51,741.9	250,909.5	7,374,072.0
Landslide	548	176,903.6	1,634,845.8	59.0	30,544.8	152,162.3	3,952,581.3
Coastal	967	170,655.9	3,212,088.4	0.0	3,988.4	21,839.3	725,038.6
Tornado	4,443	89,816.8	2,125,857.4	207.0	14,818.4	57,143.5	685,012.1
Flooding	7,836	60,000.2	1,650,261.5	78.8	7,516.9	30,128.2	444,015.0
Wildfire	1,061	57,019.4	634,813.8	210.2	18,868.0	62,445.5	1,101,922.2
Hail	4,359	52,252.7	1,544,189.1	67.2	11,298.9	49,137.7	523,857.4
Lightning	5,684	52,187.6	1,435,860.8	53.2	4,069.0	21,042.6	435,289.3
Avalanche	333	28,903.4	406,824.0	0.0	890.5	8,991.5	230,797.9
Thunderstorm	15,783	28,062.6	1,151,054.8	26.0	1,503.0	6,815.9	137,272.2
Wind	19,136	23,621.1	1,045,298.5	22.8	1,260.3	5,661.0	112,254.9
Tsunami	32	20,738.0	37,323.7	412.9	91,432.1	123,556.2	126,338.0
Fog	158	18,664.6	94,003.5	119.7	9,952.0	98,931.9	536,298.6
Winter	2,227	15,783.8	196,678.6	52.0	6,008.5	23,240.9	267,988.3
Volcano	11	1,534.0	4,817.8	11.4	444.0	16,054.7	16,054.7
	Crop Damage (thousands of $)						
Drought	316	101,935.7	309,370.8	1,869.4	260,039.3	545,714.6	1,223,556.7
Hurricane	251	52,840.1	336,693.7	0.0	15,434.6	186,448.2	1,009,937.9
Landslide	548	14,774.9	166,374.8	0.0	33.6	786.8	257,959.0
Heat	756	14,773.4	143,724.6	0.0	14.8	2,062.6	347,932.6
Fog	158	9,607.2	101,568.8	0.0	71.2	14,278.9	79,876.5
Wildfire	1,061	8,545.9	109,268.7	0.0	54.8	1,300.2	134,452.9
Coastal	967	6,646.4	75,376.8	0.0	0.0	188.7	69,204.8
Hail	4,359	5,819.2	73,221.0	0.0	693.9	4,478.9	82,608.6
Tornado	4,443	5,368.3	64,822.3	0.0	114.2	1,954.9	79,876.5
Flooding	7,836	4,262.5	80,100.5	0.0	37.5	753.1	47,258.0
Winter	2,227	3,940.2	50,781.1	0.0	0.0	379.3	75,201.3
Lightning	5,684	3,211.2	49,983.3	0.0	4.2	337.6	41,063.0
Volcano	11	2,682.2	7,783.2	0.0	1,221.8	26,096.4	26,096.4
Thunderstorm	15,783	2,436.8	50,999.0	0.0	0.6	107.3	15,049.7
Wind	19,136	2,221.4	48,236.5	0.0	0.0	58.8	13,471.7
Avalanche	333	970.9	14,317.7	0.0	0.0	0.0	1,129.4
Tsunami	32	544.7	2,408.9	0.0	0.0	2,151.3	13,471.7
Earthquake	28	0.0	0.0	0.0	0.0	0.0	0.0

Notes: This table shows summary statistics of injuries and fatalities from natural disasters by disaster-type, aggregated to the spatial cluster level. All Damage totals are in thousands of inflation-adjusted USD, and include property and crop damages. Damages data are sourced from SHELDUS, and run from 2000 through 2020.

Table IA.4: Summary Statistics on Total Disaster Damages by Hazard – Spatiotemporal Cluster-Level Data

	All Damage (thousands of $)						
	Count	Mean	SD	Median	90th Pct.	95th Pct.	99th Pct.
Hurricane	205	1,963,249.8	10,233,478.9	770.2	2,479,581.6	9,103,685.5	28,836,436.1
Drought	287	898,143.5	6,440,464.2	34,090.7	1,006,839.9	2,137,319.8	22,814,845.2
Heat	581	321,479.4	4,020,061.0	0.0	86,286.5	330,235.7	7,884,366.7
Coastal	914	293,508.1	3,474,335.0	0.0	47,078.6	289,351.0	7,427,618.9
Landslide	531	281,027.7	1,876,897.3	142.0	119,935.3	516,826.3	7,884,366.7
Earthquake	28	244,245.6	854,974.6	10,090.4	775,056.4	800,000.0	4,468,203.6
Tornado	3,601	140,534.5	2,473,059.3	208.6	33,286.5	147,319.8	1,446,102.8
Hail	3,275	110,779.0	1,970,065.6	110.6	40,033.3	158,066.1	1,436,114.5
Wildfire	1,010	97,283.6	752,906.6	353.6	41,583.8	236,637.1	2,283,272.1
Flooding	5,647	92,928.0	1,987,866.1	78.3	15,826.3	70,442.4	910,873.6
Lightning	4,318	89,451.9	1,743,610.9	50.2	10,003.3	70,677.2	1,053,624.8
Fog	155	61,794.1	252,195.4	380.5	121,939.8	280,777.7	1,810,372.9
Tsunami	28	51,198.7	92,339.7	11,410.7	170,003.3	171,338.9	426,637.6
Thunderstorm	11,598	44,486.3	1,374,608.5	23.3	2,111.5	14,613.0	349,048.6
Wind	14,399	36,436.1	1,233,626.1	20.9	1,538.8	10,623.7	288,607.9
Winter	1,914	33,297.2	267,370.3	62.9	19,040.3	86,601.0	688,621.7
Avalanche	324	32,434.4	417,199.3	0.1	3,135.3	21,368.4	264,194.4
Volcano	11	4,216.2	8,645.4	444.0	16,054.7	26,097.2	26,097.2
	Cluster Size						
Drought	287	123.7	230.0	16.0	429.0	641.0	1,038.0
Tsunami	28	90.8	136.7	7.0	297.0	321.0	510.0
Hurricane	205	80.4	169.4	2.0	356.0	527.0	633.0
Heat	581	62.5	174.5	2.0	205.0	492.0	854.0
Landslide	531	47.7	147.4	2.0	86.0	342.0	842.0
Coastal	914	46.2	148.1	1.0	77.0	403.0	754.0
Fog	155	40.9	126.9	4.0	68.0	333.0	546.0
Hail	3,275	27.8	100.1	1.0	43.0	145.0	552.0
Tornado	3,601	26.9	97.2	1.0	40.0	144.0	545.0
Wildfire	1,010	25.0	108.9	2.0	24.0	86.0	567.0
Winter	1,914	21.4	68.9	2.0	46.0	103.0	358.0
Lightning	4,318	21.4	88.1	1.0	23.0	91.0	510.0
Flooding	5,647	19.4	78.9	1.0	26.0	76.0	451.0
Avalanche	324	17.1	87.7	4.0	16.0	27.0	456.0
Thunderstorm	11,598	10.7	55.9	1.0	10.0	27.0	277.0
Wind	14,399	9.4	50.4	1.0	10.0	23.0	215.0
Earthquake	28	6.0	15.2	1.0	17.0	23.0	78.0
Volcano	11	1.7	2.1	1.0	2.0	8.0	8.0

Notes: This table shows summary statistics of damages and cluster sizes from natural disasters by disaster-type, aggregated to the spatiotemporal cluster level, conditional on the presence of the given hazard. All Damage totals are in thousands of inflation-adjusted USD, and include property and crop damages. Damages data are sourced from SHELDUS, and run from 2000 through 2020.

Table IA.5: Differences in Property Damages According to Hazard Type

	$\bar{D}_{i,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
Drought		-0.051				
		(0.202)				
Drought × $\bar{D}^{-i}_{j,t}$		-0.180*				
		(0.103)				
Heat			-0.550***			
			(0.170)			
Heat × $\bar{D}^{-i}_{j,t}$			0.136*			
			(0.080)			
Wildfire				0.234***		
				(0.082)		
Wildfire × $\bar{D}^{-i}_{j,t}$				0.215***		
				(0.038)		
Flooding					0.203***	
					(0.030)	
Flooding × $\bar{D}^{-i}_{j,t}$					0.175***	
					(0.021)	
Hurricane						-0.536***
						(0.184)
Hurricane × $\bar{D}^{-i}_{j,t}$						0.184***
						(0.040)
$\bar{D}^{-i}_{j,t}$	0.392***	0.397***	0.391***	0.387***	0.343***	0.383***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.015)	(0.014)
Log GDP	0.011	0.012	0.013	0.011	0.012	0.004
	(0.069)	(0.069)	(0.069)	(0.070)	(0.069)	(0.069)
Average Wages	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log Population	-0.053	-0.046	-0.049	-0.067	-0.095	-0.053
	(0.211)	(0.213)	(0.211)	(0.210)	(0.211)	(0.211)
Constant	-0.390	-0.478	-0.454	-0.235	-0.004	-0.277
	(2.135)	(2.142)	(2.138)	(2.121)	(2.118)	(2.129)
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	111,827	111,827	111,827	111,827	111,827	111,827
R^2	0.297	0.298	0.297	0.298	0.309	0.298

Notes: This table shows the results of a regression of log of property damages for both county-level aggregates on indicators for the presence of a hazard in a given county/cluster along with an interaction of the damage indicator with the log of property damage of that county's spatial cluster excluding that county. Damages are aggregated to the county/cluster level, and are in inflation-adjusted USD. Damages data are sourced from SHELDUS, and run from 2000 through 2020. Standard errors are double-clustered at the county- and month-level. *, **, and *** indicate 10%, 5%, and 1% significance, respectively.

Table IA.6: Differences in Crop Damages According to Hazard Type

	$\bar{D}_{i,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
Drought		2.840***				
		(0.413)				
Drought × $\bar{D}^{-i}_{j,t}$		-0.014				
		(0.068)				
Heat			-0.994			
			(0.639)			
Heat × $\bar{D}^{-i}_{j,t}$			-0.046			
			(0.252)			
Wildfire				-0.235		
				(0.482)		
Wildfire × $\bar{D}^{-i}_{j,t}$				-0.080		
				(0.143)		
Flooding					-0.016	
					(0.184)	
Flooding × $\bar{D}^{-i}_{j,t}$					0.015	
					(0.058)	
Hurricane						-1.983*
						(1.196)
Hurricane × $\bar{D}^{-i}_{j,t}$						0.025
						(0.219)
$\bar{D}^{-i}_{j,t}$	0.402***	0.396***	0.404***	0.405***	0.397***	0.416***
	(0.042)	(0.036)	(0.042)	(0.042)	(0.048)	(0.043)
Log GDP	-0.113	-0.009	-0.111	-0.124	-0.114	-0.064
	(0.258)	(0.244)	(0.258)	(0.257)	(0.258)	(0.255)
Average Wages	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log Population	-1.682**	-1.616**	-1.715**	-1.652**	-1.682**	-1.562**
	(0.770)	(0.805)	(0.773)	(0.767)	(0.771)	(0.783)
Constant	17.039**	14.358*	17.355**	16.900**	17.061**	15.188**
	(7.545)	(8.052)	(7.544)	(7.496)	(7.553)	(7.568)
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,775	11,775	11,775	11,775	11,775	11,775
R^2	0.657	0.688	0.658	0.658	0.657	0.662

Notes: This table shows the results of a regression of log of crop damages for both county-level aggregates on indicators for the presence of a hazard in a given county/cluster along with an interaction of the damage indicator with the log of crop damage of that county's spatial cluster excluding that county. Damages are aggregated to the county/cluster level, and are in inflation-adjusted USD. Damages data are sourced from SHELDUS, and run from 2000 through 2020. Standard errors are double-clustered at the county- and month-level. *, **, and *** indicate 10%, 5%, and 1% significance, respectively.